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Health Benefits and Costs of Filtration Interventions that Reduce Indoor Exposure to PM2.5 during Wildfires

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ABSTRACT

Increases in hospital admissions and deaths are associated with increases in outdoor air particles during wildfires. This analysis estimates the health benefits expected if interventions had improved particle filtration in homes in Southern California during a ten-day period of wildfire smoke exposure. Economic benefits and intervention costs are also estimated. The six interventions implemented in all affected houses are projected to prevent 11% to 63% of the hospital admissions and 7% to 39% of the deaths attributable to wildfire particles. The fraction of the population with an admission attributable to wildfire smoke is small, thus, the costs of interventions in all homes far exceeds the economic benefits of reduced hospital admissions. However, the estimated economic value of the prevented deaths exceed or far exceed intervention costs for interventions that do not use portable air cleaners. For the interventions with portable air cleaner use, mortality-related economic benefits exceed intervention costs as long as the cost of the air cleaners, which have a multi-year life, are not attributed to the short

wildfire period. Cost effectiveness is improved by intervening only in the homes of the elderly who experience most of the health effects of particles from wildfires.

Keywords: benefits, costs, health, filtration, wildfires, homes

Practical Implications

Practical and effective filtration interventions can reduce indoor exposure to particles from wildfires. These interventions are expected to substantially reduce wildfire-related hospitalizations and deaths. Public health officials may want to disseminate this information and recommend filtration interventions in homes when wildfires are burning, particularly in homes with elderly residents. At a minimum, operating existing home air filtration systems continuously during periods of wildfire smoke exposure is recommended.

INTRODUCTION

Wildfires are a large source or particles and gaseous air pollutants that temporarily increase air pollutant levels over hundreds to thousands of square miles (Confalonieri et. al. , 2007, Langmann et. al. , 2009, Delfino et. al. , 2009, Wu et. al. , 2006). Numerous studies have examined whether adverse health effects increase in populations exposed to wildfire smoke, with systematic reviews of the related literature provided by Kochi et. al. (2010) and Liu et. al. (2015). The recently published review of Liu et. al. (2015) identified 61 related epidemiological studies. In 43 of 45 studies with measures of respiratory morbidity as an outcome, there were statistically significant associations of increased respiratory morbidity with wildfire smoke exposure. Six of 14 studies reported statistically significant increases in cardiovascular morbidity and nine of 13 studies reported statistically significant increases in mortality. Among the reviewed studies, the durations and magnitudes of wildfire smoke exposure and the size of the increased risks of adverse health effects varied widely. For example, the increases in contacts with hospitals or clinics (often hospital admissions) during wildfires ranged from nil to well over 100% and increases in mortality ranged from less than 1% to approximately 50%. In general, the elderly and young children were found to more often experience adverse health effects.

Johnston et. al. (2012) estimated that particles from wildfires increase global death rates by 339,000 per year; although this estimate relied on relationships of particle concentrations with mortality not specific to wildfires.

Studies of the health effects of wildfires have compared incidence of health outcomes during periods with and without wildfire smoke exposure, often in comparison to control populations with no wildfire smoke exposure during the same time periods. Often, the exposure metric has been dichotomous, i.e., exposed or not exposed to wildfire smoke. Some studies have assessed the associations of health outcomes with particle levels during periods with and without wildfire smoke exposure, e.g., (Kochi et. al., 2010, Delfino et. al., 2009, Rappold et. al. , 2014) and other studies reviewed by Liu et. al. (2015).

Most of wildfire-health literature assumes that adverse health effects are largely a consequence of increased particle exposures. This expectation is consistent with the very high concentrations of particles and more moderate concentrations of gaseous pollutants, although, data on gaseous pollutants from wildfires are sparse. This expectation appears to also be driven by the finding that particles in general urban air are a larger source of adverse health effects than gaseous air pollutants (EPA, 2011a) and is to a limited extent supported by mechanistic evidence (Tan et. al. , 2000, Swiston et. al. , 2008, Kim et. al. , 2014).

The adverse health effects of wildfire smoke are expected to increase as the climate changes due to increases in the number and severity of wildfires (Fisk 2015). Spracklen et. al. (2009) estimated that, by 2050, climate change will cause a 54% increase in the average area burned in the western United States.

Given the demonstrated adverse health consequences of wildfires that are expected to increase with climate change, information on the effectiveness of mitigation options is needed. This paper estimates the potential health benefits and costs of improving particle filtration in homes. The analysis is performed for a six-county region in Southern California with substantially increased particle concentrations during wildfires in 2003. This particular wildfire case is employed for the evaluation because particle levels in the exposed population have been assessed in detail (Wu et. al., 2006), hospital admission rates have been related quantitatively with particle levels (Delfino et. al., 2009), and effects on mortality have been estimated (Kochi et. al. , 2012).

METHODS

Interventions and Model Description

This analysis estimates the magnitude of reduced hospital admissions and premature deaths that would have occurred if residential indoor particle filtration interventions had been implemented in the homes of six Southern California counties during a wildfire in year 2003. Mass balance models are used to estimate the mass concentrations of particles, from outdoor air, less than 2.5 µm in diameter (PM2.5) in homes with and without interventions. Other mass balance models estimate PM2.5 concentrations at non-home indoor locations, and in vehicles. Total inhalation intake of PM2.5 from outdoor air is calculated, accounting for time spent in different environments and inhalation rates. Assuming that health effects are proportional to total PM2.5 intake, the interventions are associated with equivalent reductions in outdoor air PM2.5 levels during the wildfire event. These projections are used together with published relationships between hospital admission rates and outdoor air PM2.5 levels during the 2003 wildfire, to estimate the fractional reductions in hospital admissions associated with the interventions. The fractional reductions in admission are combined with data on numbers of admissions, to estimate the avoided hospital admissions. Additionally, the projected reductions in PM2.5 intake are used together with a published estimate of excess deaths from the 2003 Southern California wildfire, to estimate the deaths prevented by the interventions. Intervention costs and health-related financial benefits are also estimated. Calculations are performed assuming interventions in all homes. Since a large majority of the wildfire-related hospitalizations (Delfino et. al., 2009) and deaths (Kochi et. al., 2012) associated with the 2003 Southern California wildfires occurred for residents with age greater than or equal to 65, additional calculations were performed assuming interventions in the 22% of homes in the study area with residents in this age range (U. S. Census Bureau, 2014).

The interventions reduce exposures to particles that are generated by the wildfire and exposures to particles from other sources. Thus, the health effects prevented by the interventions are health effects associated with PM2.5 from the wildfire and from other sources during the wildfire period.

Table 1 summarizes the baseline and intervention conditions and links interventions to baseline conditions. We assume that windows are maintained closed during the period of wildfire smoke exposure and that the home is ventilated by air infiltration, since a very small fraction of homes have mechanical ventilation. In the first baseline (B1), the home has an intermittently operating central forced air heating and cooling system with a typical low-efficiency particle filter. In the second baseline (B2), the home has no central forced air system. Baseline case B2 may also apply to homes with a moderate amount of use of window air conditioners as the limited available literature indicates low rates of PM2.5 removal by window air conditioners (Mak et. al. , 2011, Batterman et. al. , 2012).. Interventions i1 – i5 use B1 as the reference. In intervention 1 (i1), the forced air heating and air conditioning system fan is operated continuously during the period of wildfire smoke exposure with no change in the type of filter in the system. In i2, the forced-air fan is operated continuously and the filter is upgraded to a high-efficiency filter. In i3, the filter is upgraded to a high efficiency filter but the forced air system operates in its normal intermittent mode. In i4, a portable air cleaner with fan and particle filter is operated in the home during the period of wildfire smoke exposure and the forced air heating and air conditioning system fan operates continuously with no filter system upgrade. In i5, a portable fan filter unit is operated in the home during wildfire smoke exposure, the forced air heating and air conditioning system fan operates continuously, and the filter in the forced-air system is upgraded to a high efficiency filter. Intervention i6 uses B2 as the reference. In i6, a portable fan filter unit is operated in the home during the period of wildfire smoke exposure and the home has no forced air system with filtration.

Table 1. Baseline and intervention conditions.

Baseline or Intervention code	Reference Condition	Conditions		
		Forced Air System Operation	Efficiency of Filter in Forced Air System	Continuously Operating Portable Air Cleaner
B1	NA	Intermittent	Typical low	No
B2	NA	No forced air	NA	No
i1	B1	Continuous	Typical low	No
i2	B1	Continuous	Upgraded to high	No
i3	B1	Intermittent	Upgraded to high	No
i4	B1	Continuous	Typical low	Yes
i5	B1	Continuous	Upgraded to high	Yes
I6	B2	No forced air	NA	Yes

In subsequent text, all references to indoor or in-vehicle particle concentrations are concentrations of particles originating from the outdoor air. For baseline cases, the residential indoor air concentrations of PM2.5 were estimated using equations 1 - 4, based on steady state mass balances for a well-mixed indoor air volumes.

$$C_{B1} = K_{B1}\, C_O \quad (1)$$

$$C_{B2} = K_{B2}\, C_O \quad (2)$$

$$K_{B1} = P\, \lambda_V \,/(\lambda_V + \lambda_D + \lambda_F) \quad (3)$$

$$K_{B2} = P\, \lambda_V\, /(\lambda_V + \lambda_D) \tag{4}$$

where C_{B1} and C_{B2} are the residential indoor PM2.5 concentrations of particles from outdoors in baseline cases B1 and B2 without any interventions, P is the particle penetration factor, i.e., the fraction of particles that penetrate through the building envelope during air infiltration (dimensionless), λ_V is the ventilation rate, λ_D is the rate of particle removal by deposition on indoor surfaces, and λ_F is the rate of particle removal by the home's forced air heating and air conditioning system in the absence of an intervention. In these and subsequent equations, particle concentration are in units of μg m^{-3}, and all λ parameters are normalized by the indoor volume and have units of h^{-1}. The parameter λ_F is calculated from equation 5

$$\lambda_F = Q\, D\, \varepsilon_L \tag{5}$$

where Q is the air flow rate of the forced air heating and air conditioning system divided by the indoor volume, D is the fraction of time that the forced air fan operates, sometimes called the duty cycle, and ε_L is the PM2.5 removal efficiency of the low efficiency filter normally used in the forced air system, i.e., unaffected by an intervention.

Because we assume that the health effects depend on the total inhalation intake of particles, we require estimates of particle concentrations when indoors and away from the home, e.g., when at work, school, or in stores. We assume these buildings have air infiltration plus continuous mechanical outdoor air ventilation and indoor air recirculation, with the incoming outdoor air and recirculated air passing through a particle filter. Under these conditions, the mass balance equation for the indoor concentrations of particles is

$$C_W = K_W\, C_O \tag{6}$$

with

$$K_W = ((1 - \varepsilon_W)\lambda_{MW} + \lambda_{IW}P)/(\lambda_{IW} + \lambda_{MW} + \lambda_{DW} + \varepsilon_W \lambda_{RW}) \quad (7)$$

where C_W is the indoor concentration at work, school, or other indoor non-residential locations, ε_W is the PM2.5 removal efficiency of the particle filter, λ_{MW} is the flow rate of outdoor air supplied mechanically, λ_{IW} is the air infiltration rate and λ_{DW} is the particle deposition rate in buildings other than homes, and λ_{RW} is the mechanical recirculation air flow rate in buildings other than homes. The total ventilation rates in buildings other than homes, denoted λ_{VW}, equals the sum of λ_{MW} and λ_{IW}, thus, we will be required to assume a partitioning of measured values of λ_{VW} into λ_{MW} and λ_{IW}.

The particle concentration in vehicles (C_V) is estimated as a fraction of the outdoor air concentration, i.e.,

$$C_V = K_V\, C_O \quad (8)$$

with K_V based on empirical data.

For intervention cases i1-i6, the residential indoor particle concentrations C_N are calculated as follows

$$C_N = K_N\, C_o \quad \text{for N = 1 – 6} \quad (9)$$

$$K_N = P\, \lambda_V / (\lambda_V + \lambda_D + \lambda_N) \quad \text{for N = 1 to 6} \quad (10)$$

with λ_N, for N = 1 to 6, equal to the rates of particle removal by filtration during interventions i1 through i6, respectively. Values of λ_N are calculated as follows

$$\lambda_1 = Q\ \varepsilon_L \quad (11)$$

$$\lambda_2 = Q\, \varepsilon_H \quad (12)$$

$$\lambda_3 = Q\, D\, \varepsilon_H \tag{13}$$

$$\lambda_4 = Q\, \varepsilon_L + Q_P\ \varepsilon_P \tag{14}$$

$$\lambda_5 = Q\, \varepsilon_H + Q_P\ \varepsilon_P \tag{15}$$

$$\lambda_6 = Q_P\ \varepsilon_P \tag{16}$$

where ε_H is the PM2.5 removal efficiency of the higher efficiency filter in the forced air system during interventions i2, i3, and i5, Q is the air flow rate in the forced air heating and cooling system divided by the indoor volume, Q_p is the air flow rate of the portable air cleaning system divided by indoor volume, and ε_p is the PM2.5 removal efficiency of the portable air cleaner.

The decrease in indoor PM2.5 concentration as a consequence of interventions equals C_{B1} minus C_N for interventions 1 through 5 and C_{B2} minus C_6 for intervention 6. However, as discussed subsequently, changes in hospital admission rates have been related to changes in outdoor PM2.5 concentrations during a wildfire, even though the outdoor air PM2.5 concentration is not an accurate indicator of actual total PM2.5 exposure. We assume that hospital admission rates from wildfire smoke exposure are proportional to total intake of PM2.5 from wildfires. PM2.5 intake in each environment is the product of the inhalation rate, PM2.5 concentration, and time spent in that environment, and the total PM2.5 intake is the sum of the PM2.5 intake when outdoors, at home, at other indoor locations, and in vehicles. We separate time at home into time at sleep and time at home awake, because inhalation rates are diminished when sleeping. Thus, for baseline cases B1 and B2, and for interventions i1 through i6, total PM2.5 intake is calculated as follows

$$I_{B1} = C_O(B_O\, T_O + B_S\, K_{B1}\, T_S + B_{HA} K_{B1} T_{HA} + B_W K_W T_W + B_V\, K_V\, T_V) \tag{17}$$

$$I_{B2} = C_O(B_O\, T_O + B_S\, K_{B2} T_S + B_{HA} K_{B2} T_{HA} + B_W K_W T_W + B_V\, K_V\, T_V) \tag{18}$$

$$I_N = C_O\,(B_O\,T_O + B_S K_N\,T_S + B_{HA} K_N T_{HA} + B_W K_W T_W + B_V\,K_V\,T_V) \quad \text{for N = 1 to 6} \tag{19}$$

where: I_{B1} and I_{B2} are the PM2.5 intake for baseline conditions B1 and B2; I_N is the PM2.5 intake for intervention N; B_O, B_S, B_{HA}, B_W, B_V are inhalation rates when outdoors, at home asleep, at home awake, at work and other indoor locations, and in vehicles; and T_O, T_S, T_{HA}, T_W, and T_V are the times spent in the same environments.

Because hospital admission rates have been related to outdoor air PM2.5 concentration, to estimate the health benefits of interventions we calculate an effective outdoor air PM2.5 concentration, designated C_{OE}, that produces an intake for PM2.5 equal to I_N. The interventions reduce PM2.5 intake by ΔI, where

$$\Delta I = I_{B1} - I_N = C_O(B_S\,T_S + B_{HA}\,T_{HA})\,(K_{B1} - K_N) \quad \text{for N= 1 to 5} \tag{20}$$

$$\Delta I = I_{B2} - I_N = C_O\,(B_S\,T_S + B_{HA}\,T_{HA})\,(K_{B2} - K_6) \quad \text{for N = 6} \tag{21}$$

For baseline B1, applicable to i1 – i5, reducing C_O to C_{OE} reduces PM2.5 intake by

$$\Delta I = (B_O\,T_O + B_S\,K_{B1}\,T_S + B_{HA}\,K_{B1}\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V\,)(C_O - C_{OE}) \tag{22}$$
for N = 1 - 5

and for baseline B2 applicable to i6, reducing C_O to C_{OE} reduces PM2.5 intake by

$$\Delta I = (B_O\,T_O + B_S\,K_{B2}\,T_S + B_{HA}\,K_{B2}\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V\,)(C_O - C_{OE}) \tag{23}$$
for N = 6

Combining equations 20 and 22 and solving for C_{OE} yields

$$C_{OE} = \frac{C_O\,(B_O\,T_O + B_S\,K_N\,T_S + B_{HA}\,K_N\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V)}{(B_O\,T_O + B_S\,K_{B1}\,T_S + B_{HA}\,K_{B1}\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V} \quad \text{for N = 1 to 5} \tag{24}$$

Similarly, combining equations 21 and 23 and solving for C_{OE} yields

$$C_{OE} = \frac{C_O\,(B_O\,T_O + B_S\,K_6\,T_S + B_{HA}\,K_6\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V)}{(B_O\,T_O + B_S\,K_{B2}\,T_S\;\; B_{HA}\,K_{B2}\,T_{HA} + B_W\,K_W\,T_W + B_V\,K_V\,T_V} \quad \text{for N = 6} \tag{25}$$

We employ measures of risk determined from studies of the 2003 Southern California wildfire to relate PM2.5 concentrations with adverse health effects. Risk parameters based on the many studies of how typical urban particle levels influence health may not apply for wildfire periods of shorter duration with particles that may differ physically and chemically from typical urban air particles. Delfino et. al. (2009) evaluated the relationship of hospital admission rates for various health outcomes, e.g., asthma, pneumonia, with outdoor air PM2.5 concentrations during the 2003 Southern California wildfire, while controlling for other factors. For the six-county study region, they provide fractional increases in hospital admission rates during the wildfire period per 10 μg m^{-3} increase in outdoor air PM2.5 concentrations, as well as average PM2.5 concentrations in each county, before, during, and after the wildfire. Using population data for each county as reported in the 2000 Census, county-population-weighted average PM2.5 concentrations during wildfire and non-wildfire periods were 56.9 and 21.6 μg m^{-3}. The fractional change in hospital admissions for health outcome "j" per 10 μg m^{-3} change in outdoor air PM2.5 concentration will be denoted X_j. Thus, the fractional reductions in hospital admission rates R_j expected from a filtration intervention are calculated from the expression

$$R_j = 0.1\, X_j\, (C_o - C_{oe}) \qquad (26)$$

with the PM2.5 concentrations in units of micrograms per cubic meter. For comparison, limited supplemental calculations were also performed based on an exponential dose-response relationship, which is commonly used for particles (Abt Associates, 2003)

$$R_j = Exp(\beta\, \Delta PM) - 1 \qquad (26b)$$

where β is a coefficient determined from empirical data and ΔPM is the change in particle concentration. For our application, ΔPM was replaced by the change in C_{OE} and β was derived from the values of X_j. in Delfino et. al. (2009).

Equation 27 is used to estimate the numbers of prevented admissions S_j to the hospital when an intervention is implemented,

$$S_j = R_j N_j \qquad (27)$$

where N_j is the total number of hospital admissions for outcome j during the wildfire period with N_j calculated as indicated subsequently in equation 29. Delfino et. al. (2009) provided values of total admissions A_j for their total study period which included 20 days before the wildfire, 10 days during the wildfire, and 16 days after the wildfire. They also provided relative rates RR_j of hospital admissions for each health outcome for each of the three time periods, assigning a relative rate of unity to the pre-wildfire period. Using this information, the numbers of hospital admissions (N_j) for health outcome j during the wildfire period were estimated as follows

$$A_j = 20\, Y_j + 10\, RR_{j,wildfire} Y_j + 16\, RR_{j,post\ wildfire}\, Y_j \qquad (28)$$

$$N_j = 10\, RR_{j,wildfire}\, Y_j \qquad (29)$$

with Y_j equal to the number of admissions per day for outcome j in the pre-wildfire period.

The economic value of prevented hospital admissions V_T is calculated from the numbers of prevented admissions and the unit value U_j of prevented admissions.

$$V_T = \sum_j S_j\ U_j \qquad \text{for j = 1, or for j= 2-5} \qquad (30)$$

where j equals one for all respiratory admissions and values of j from two to five indicate specific types of respiratory admissions described subsequently in Table 3.

Kochi et. al. (2012) estimated that the wildfires in Southern California during 2003 were associated with 133 excess cardio-respiratory deaths with 95% confidence limits of 26 to 262, with a normal distribution. The number of cardio-respiratory deaths in the reference period was 536, consequently the increase of 133 deaths is a 25% increase. Assuming that this association is valid and that excess deaths vary in proportion to total PM2.5 intake, the number of deaths M_N prevented by interventions 1 through 6 are estimated with the following equation

$$M_N = 133\ (I_{B1} - I_N) /\ I_{B1} \qquad (31)$$

For comparison, limited calculations were performed assuming an exponential dose-response relationship

$$M_N = \ M_{REF}\ (EXP\ (\alpha\ \Delta PM) - 1) \qquad (31b)$$

where M_{REF} is reference number of deaths in the absence of wildfire pollution and α is determined from empirical data. Kochi et. al. (2012) did not provide sufficient data to calculate α; however, their data enabled calculation of the product of α and ΔPM. For interventions, the product of α and ΔP was down-scaled as follows

$$(\beta\ \Delta PM)_N = (\beta \Delta PM)_B\ (1 - \frac{I_B - I_N}{I_B}) \qquad (31c)$$

where subscripts N and B refer to the intervention number and baseline case, respectively.

The economic value of prevented deaths F_N is

$$F_N = \ M_N\ U_D \qquad (32)$$

where U_D is the unit value of an avoided death.

For intervention i1, the only expense is the cost of operating the fan of the central forced air heating and cooling system continuously, as opposed to intermittently as needed for air conditioning, during the ten-day period of wildfire smoke exposure. Thus,

$$E_1 = 240\,(1-D)\,Z\,Q\,V\,(1/3600)\;G \tag{33}$$

where E_1 is the expense (\$), 240 equals the hours in the 10-day period of wildfire smoke exposure, Z is the power consumption of the fan per unit air flow (W m^{-3} s^{-1}), V is the house volume (m^3), G is the electricity price (\$ per Watt-hour) and 3600 is a conversion factor (seconds per hour). We assume the same cost of operating the forced air fan continuously in intervention i2 despite the higher efficiency filter in i2. In some forced air systems, with a higher efficiency and higher pressure-drop filter installed the air flow rate will decrease modestly and fan power will also decrease modestly (Stephens et. al. , 2010, Walker et. al. , 2013). In other forced air systems that automatically seek to maintain the air flow rate constant as pressure drop increases, fan power will increase modestly (Stephens et. al., 2010, Walker et. al., 2013). In i2, there is an incremental expense (E_H) for the high efficiency filter relative to a standard low efficiency filter. Therefore,

$$E_2 = E_1 + E_H \tag{34}$$

For intervention i3, the only expense is the incremental cost of the higher efficiency filter

$$E_3 = E_H \tag{35}$$

For intervention i4, the expense is

$$E_4 = E_1 + 240\,Z_P\,Q_P\,V\,(1/3600)\,G + E_P \tag{36}$$

where Z_P is the power consumption of the portable air cleaner fan per unit air flow (W m^{-3} s^{-1}) and E_P is the cost of the portable air cleaner. For i5 and i6, the expense is

$$E_5 = E_2 + 240\,Z_P\,Q_P\,V\,(1/3600)\,G + E_P \tag{37}$$

$$E_6 = 240\, Z_P\, Q_P\, V\, (1/3600)\, G + E_P \tag{38}$$

Equations 33 through 38 indicate intervention costs per housing unit. Total costs are determined by multiplying with the number of housing units in the six-county region or by 22% of this number (U. S. Census Bureau, 2014) for the subpopulation with age greater than or equal to 65.

Model inputs and calculation methods

Many model inputs were required to implement the mass balance and inhalation rate calculations. Tables 2 provides parameter values or distributions and the Supplemental Information provides associated charts, detailed descriptions of the basis for parameter values, and applicable references. For housing characteristics, data from Southern California homes were used when possible. We assumed that windows are maintained closed during the period of wildfire smoke exposure. For interventions i2, i3 and i5, we assumed use of a higher efficiency filter, with a Minimum Efficiency Reporting Value (MERV) rating of 12, in the forced air systems of homes. Based on estimates of the extent of air leakage around filters in residential forced air systems, VerShaw et. al. (2009) estimated that the effective Initial Efficiency Reporting Value (IERV) of IERV 11 filters is typically reduced by three units to IERV 8. The IERV value is the MERV value of a clean (unused) filter. Accordingly, we assumed a three-unit reduction in the effective MERV rating for a MERV 12 filter, resulting in an effective MERV value of 9. For interventions i4 through i6, a portable fan filter unit with HEPA filter is operated. We assumed that the product of the unit's air flow rate and particle removal efficiency divided by the indoor air volume is 1 h^{-1}. We also assumed that people have the same average inhalation rate when awake at home, at other indoor locations, and in vehicles.

Table 2. Values for parameters in mass balance and inhalation rate calculations*.

Parameter	Value(s)	Parameter	Value(s)	Parameter	Value(s)
λ_V (h^{-1})	GM 0.60 GSD 2.32	ε_L (-)	AM 0.12 SD 0.06	T_O (%)	7.5, 7.2, 0***
λ_{VW} (h^{-1})	GM 1.06 GSD 2.56	ε_H (-)	AM 0.27 SD 0.12	T_V (%)	5.5, 5.9, 0***
λ_{IW} (h^{-1})	0.1	ε_P Q_P (h^{-1})	1.0	B_S (m^3 h^{-1})	0.58, 0.61, 0.52***
λ_{RW} (h^{-1})	AM 3.42 SD 2.79	ε_W (-)	AM 0.27 SD 0.12	B_{HA} (m^3 h^{-1})	0.71, 0.75, 0.64***
λ_D (h^{-1})	AM 0.39 SD 0.08	K_V (-)	AM 0.6 SD 0.06**	B_W (m^3 h^{-1})	0.71, 0.75***
λ_{DW} (h^{-1})	AM 0.39 SD 0.08	V (m^3)	GM 404 GSD 1.47	B_O (m^3 h^{-1})	0.83, 0.86***
P (-)	AM 0.97 SD 0.06**	T_S (%)	37.0, 34.6, 36.2***	B_V (m^3 h^{-1})	0.71, 0.75***
Q (h^{-1})	GM 4.36 GSD 1.44	T_{HA} (%)	32.0, 33.6, 63.8***	C_O (μg m^{-1})	56.9
D (h^{-1})	AM 0.18 SD 0.09	T_W (%)	17.7, 18.6, 0***		

*GM = geometric mean, GSD = geometric standard deviation, AM = arithmetic mean, SD = standard deviation
**cropped normal distribution with minimum of zero and maximum value of 1.0
***first value is for all ages, second value is for age greater than 20, third value is for age ≥65, see supplemental information for more details

Values of the parameters from Delfino et. al. (2009) used to estimate hospital admission rates with outdoor air PM2.5 concentrations are provided in Table 3.

Table 3. Values of parameters used to relate PM2.5 levels with hospital admissions.

Type of Admission	X_j (95% CI)	$RR_{j,wildfire}$ (95% CI)	$RR_{j,post\text{-}wildfire}$ (95% CI)	A_j
All respiratory (j=1)	0.028 (0.014 – 0.041)	0.961 (0.916 – 1.008)	1.143 (1.072 – 1.219)	21019
Asthma (j = 2)	0.048 (0.021 – 0.076)	1.088 (0.965 – 1.227)	1.264 (1.085-1.473)	3022
Acute bronchitis or bronchiolitis (j=3)	0.096 (0.018 – 0.179)	1.143 (0.878 – 1.490)	1.482 (1.042-2.109)	618
COPD,age 20-99 (j=4)	0.038 (0.004 – 0.075)	0.988 (0.875 – 1.115)	1.043 (0.885-1.228)	2860
Pneumonia (j = 5)	0.028 (0.007 – 0.050)	0.943 (0.868 – 1.025)	1.294 (1.158-1.446)	6440

Note: values of X_j are per 10 μg m^{-3}.

In the calculations for age greater than and equal to 65, we used values of X_j, $RR_{j,wildfire}$, $RR_{j,postwildfire}$, and A_j from Tables 3 and 4 of Delfino et. al. (2009) for that age range. For these calculations, we assumed that, with and without an intervention, this elderly subpopulation remained indoors at home 100% of the time during the period of wildfire smoke exposure, asleep 36.2% of the time (EPA, 2011b), although in general this population is indoors at home 81% of the time (Klepeis et. al. , 2001).

Table 4 provides values for parameters used in the economic benefit and cost benefit analysis. The costs for respiratory hospital admissions are costs per admission adjusted to year 2003 based on the medical care consumer price index (U.S. Census Bureau, 2012). Energy, airflow, and cost data for two different portable air cleaners were considered for interventions i4 – i6. The less expensive Brand X unit contains a prefilter that incorporates activated carbon and a high efficiency particle filter. The more expensive Brand Y unit contains a prefilter, a high efficiency particle filter and limited media to remove gaseous pollutants, and has a more energy efficient fan system. We assumed that to provide one indoor air volume per hour of filtered air the air cleaner's clean air delivery rate for smoke in cubic meters per hour must equal the house volume in cubic meters. The clean air delivery rate is a performance metric available for most air cleaners. The cost values for air cleaners in Table 4 are for a typical 433 m^3 house. The Brand X air cleaner has a clean air delivery rate for smoke that was 24% above 433 m^3 h^{-1}, thus, in Table 4 the published unit cost was divided by 1.24. The Brand Y air cleaner has a clean air delivery rate for smoke that was 76% of 433 m^3 h^{-1}, so the unit cost in Table 4 was divided by 0.76. In the modeling, air cleaner costs and energy use were scaled with house volume.

Table 4. Parameter values for cost-benefit analysis.

Parameter	Value	Reference(s)	Comment
All respiratory admission ($)	22,300	(RTI International, 2015)	Year 2000 dollars adjusted to 2003
Asthma admission ($)	12,800	(RTI International, 2015)	Year 2000 dollars adjusted to 2003
Bronchitis or bronchiolitis admission ($)	7,100	(Hasegawa et. al. , 2013)	Geometric mean value for bronchiolitis in 2003, median is $6637
COPD admission ($)	14,100	(EPA, 2011a)	Year 2006 dollars adjusted to 2003
Pneumonia admission ($)	20,000	(RTI International, 2015)	Year 2000 dollars adjusted to 2003
Premature death ($)	8.04 million	(Industrial Economics Inc., 2011)	Linear interpolation between estimates for 1990 and 2020
Z (W m^{-3} s^{-1})	1,090	(Proctor and Parker, 2000)	Weighted average of values measured in three studies
G ($ W^{-1} h^{-1})	0.000132	(Energy Information Administration, 2015)	Average residential electricity retail price in 2003 in California
E_H ($)	$3.30	Airfiltersdelivered.com Discount air filters.com	Average of price for MERV 11 and MERV 13 filters minus average of price MERV 6 or MERV 8 filters, all for mid-size 2.54 cm deep filters
Z_P (W m^{-3} s^{-1})	602 495	www.air-purifiers-america.com manufacturer's specifications	For Brand X For Brand Y
E_P ($)	239 607	www.air-purifiers-america.com www.allergyandair.com	For Brand X For Brand Y
Housing units	6.92 million	http://censtats.census.gov/cgi-bin/usac/usatable.pl	Total housing units in 2003 in six-county region

The model was implemented using R software. Distributions of PM2.5 inhalation intake rates in homes and in other microenvironments were modeled by sampling from distributions of input parameters, as specified in the supplemental material. Sampling from the distribution of input parameters was continued until results of calculations were stable within three significant figures. The resulting distributions of PM2.5 intake rates were used to calculate values of the population mean effective outdoor air PM2.5 concentrations (C_{OE}) that correspond to intake rates of PM2.5 for the different interventions considered. Estimated reductions in hospital admissions and premature deaths were calculated using the population mean C_{OE} values for the different interventions. For each intervention, cost savings were computed for prevented hospital admissions and prevented premature deaths. The 95% confidence intervals that we provide for prevented hospital admissions and prevented deaths, and the 95% confidence intervals in the associated costs savings from prevented admissions and deaths, are based only on the confidence intervals of Delfino et. al. (2009) for the values of X_j and the confidence intervals of Kochi et. al. (2012) for number of deaths. The distributions of other model input parameters were assumed to primarily reflect variability, rather than uncertainty. Consequently, our 95% confidence intervals do not account for all sources of uncertainty. The central estimates of cost of interventions and the corresponding 5th and 95th percentile estimates were computed for the homes modeled by calculations that again sampled from the distributions of input parameters.

RESULTS

Table 5 provides mean, median, and fifth and ninety fifth percentile PM2.5 concentrations in each environment type, and in the homes with and without the interventions. Figure A11 in the Supplemental information shows the distributions graphically. The percentage reductions in mean PM2.5 concentrations in homes associated with the interventions, also in Table 5, range from 11% to 62%. The nearly no-cost option (i1) of running the HVAC fan continuously with no upgrade in filter efficiency reduces the mean PM2.5 concentration by 24% while continuous fan operation plus a filter efficiency upgrade (i2) approximately halves the PM2.5 concentration. Upgrading the filter efficiency without continuous fan operation (i3) leads to only an 11% reduction in mean particle concentrations. Use of portable continuously operating air cleaners in combination with continuous HVAC operation with low efficiency filters (i4), and high efficiency filters (i5), reduces mean PM2.5 concentrations by 51% and 62%, respectively. The portable air cleaner, reduces the predicted mean PM2.5 concentration by 45%, in homes without forced air HVAC systems (i6).

Table 5. Predicted PM2.5 concentrations (µg m^{-3}).

Environment	Mean	% Decrease	Median	5^{th} Percentile	95^{th} Percentile
Work/School*	21.5	--	20.8	5.8	39.6
Vehicle	34.1	--	34.1	28.5	39.8
Home Baseline 1	29.2	--	29.6	12.1	45.2
Home Baseline 2	31.9	--	32.6	14.6	46.8
Home i1	22.1	24	21.3	6.8	40.2
Home i2	15.5	47	13.8	3.7	33.0
Home i3	26.1	11	26.0	9.5	43.2
Home i4	14.2	51	12.7	3.7	30.0
Home i5	11.2	62	9.5	2.6	25.5
Home i6	17.4	45	16.1	5.2	33.9

*and other non-residential indoor locations

Table 6 provides the predicted time-average PM2.5 intake rates. Because the interventions have no influence on PM2.5 intake away from the home, for the all-age population, the percentage reductions in PM2.5 intake rates associated with the interventions are approximately 60% of the percentage reductions in PM2.5 concentrations in the homes. Table A3, in the supplementary information, provides the corresponding values of effective outdoor-air PM2.5 concentration. Note that for intervention i5, the effective outdoor-air PM2.5 concentration for the population with age greater than or equal to 65 is below the background level of PM2.5 concentration reported for the period without wildfire smoke exposure.

Table 6. Time average PM2.5 intake rates (μg h^{-1}).

Condition	All ages					Age > 20					Age ≥ 65				
	Mean	% Reduc-tion	Median	5th %ile	95th %ile	Mean	% Reduc-tion	Median	5th %ile	95th %ile	Mean	% Reduc-tion	Median	5th %ile	95th %ile
B1	20.5	--	20.7	12.7	27.9	21.6	--	21.7	13.3	29.4	17.4		17.6	7.2	27.0
B2	21.7	--	22	13.8	28.7	22.8	--	23.1	14.5	30.2	19.0		19.4	8.7	27.9
i1	17.4	15	17.1	10.2	25.7	18.3	15	18	10.8	27	13.2	24	12.7	4.1	24.0
I2	14.4	30	13.8	8.6	22.4	15.2	30	14.5	9.1	23.6	9.2	47	8.2	2.2	19.7
i3	19.2	6	19.1	11.5	27	20.1	7	20.1	12.1	28.4	15.6	11	15.5	5.7	25.8
i4	13.9	32	13.3	8.6	21.2	14.6	32	14	9	22.3	8.5	51	7.5	2.2	17.9
i5	12.6	39	12	7.9	19.2	13.2	39	12.6	8.3	20.2	6.7	62	5.7	1.5	15.3
I6	15.3	29	14.8	9.4	22.9	16	30	15.5	9.8	24	10.4	45	9.6	3.1	20.3

The estimated total numbers of hospital admissions and wildfire-related excess deaths during the wildfire period, and the estimated numbers of admissions and deaths prevented by the interventions, are provided in Table 7. With interventions implemented in all homes, total (all types of respiratory) hospital admissions decrease by 47 to 261 and the estimated numbers of prevented deaths range from 9 to 52. For the interventions only in homes of residents with age greater than or equal to 65, the estimate of prevented hospitalizations due to pneumonia and prevented deaths are even larger than for the case of interventions in all homes. Larger predicted health benefits occur for these outcomes because a large majority of the health effects occur in the elderly and because, for the scenario with interventions only in homes of the elderly, we assumed that the elderly remained indoors at home throughout the period of wildfire smoke exposure, making the interventions more effective in reducing PM2.5 intake. Table A4 in the Supplemental Information provides percentage reductions in the increases in wildfire-related hospital admissions and deaths for each intervention. For interventions in all homes and considering the full exposed population, hospital admissions are decreased by 11% to 63% of the increase in admissions during the wildfire period, and deaths are decreased by 7%

to 39% of the increase in deaths during the wildfire period. For interventions only in homes with residents age 65 and older, and considering only this sub-population, hospital admissions are decreased by 20% to 105% of the increase in admissions during the wildfire and deaths are decreased by 12% to 65% of the increase in deaths during the wildfire period. For intervention i5 and the elderly population, prevented hospital admissions exceed the increase in admissions during the wildfire, because the intervention reduces PM2.5 intake below the level reported for periods without a wildfire. Calculations based on exponential dose-response equations, in place of the linear equations, yielded very similar prevented admissions and deaths. For the all-respiratory category of admissions and the full (all-age) population, the exponential model yielded percentage reductions in hospital admissions that were one to two percentage points larger than the linear model, corresponding to a relative 4% more prevented admissions. For deaths, the exponential model yielded percentage reductions in deaths that were one to three percentile points larger than the linear model, with the maximum relative increase of 9% in prevented deaths.

Table 7. Estimated baseline numbers of hospital admissions and wildfire-caused premature deaths during the wildfire period and estimated reductions due to the interventions.

Outcome	Baseline total admissions during wildfire*	Baseline increased admissions or deaths during wildfire	Interventions – Number of cases prevented (95% confidence interval)					
			i1	i2	i3	i4	i5	i6
Interventions in all homes								
All respiratory	4217 (3993-4454)	417 (265-655)	106 (67-167)	201 (128-317)	47 (30-74)	219 (140-345)	261 (166-411)	202 (129-318)
Asthma	643 (561-738)	109 (62-192)	28 (16-49)	53 (30-93)	12 (7-22)	57 (33-101)	68 (39-120)	53 (30-93)
Acute bronchitis and bronchiolitis	128 (94-175)	43 (19-99)	11 (4.9-25)	21 (9.2-48)	4.9 (2.1-11)	23 (10-52)	27 (12-62)	21 (9.3-48)
COPD (Age ≥ 20)	607 (529-696)	81 (32-207)	21 (8.1-52)	39 (15-100)	9.1 (3.6-23)	43 (17-108)	51 (20-129)	39 (16-100)
Pneumonia	1211 (1100-1334)	120 (56-257)	30 (14-65)	58 (27-124)	13 (6.3-29)	63 (29-135)	75 (35-161)	58 (27-124)
Premature death	--	133 (26-262)	21 (4.1-41)	40 (7.8-79)	9.3 (1.8-18)	43 (8.5-86)	52 (10-102)	40 (7.8-79)
Interventions in homes with residents age ≥ 65								
All respiratory	1829 (1684 - 1988)	194 (105-358)	84 (46 - 156)	158 (85 - 291)	38 (20 - 70)	171 (93 - 317)	203 (110 -375)	152 (82 - 281)
Asthma	108 (78 - 148)	38 (18-81)	17 (7.9 - 35)	31 (15 - 66)	7.4 (3.5 - 16)	34 (16 - 71)	40 (19 - 84)	30 (14 - 63)
Acute bronchitis and bronchiolitis	34 (18 - 66)	17 (7-46)	7.5 (2.9 - 20)	14 (5.3 - 37)	3.4 (1.3 - 9.0)	15 (5.8 - 40)	18 (6.9 - 48)	14 (5.2 - 36)
COPD (Age ≥ 20)	427 (363 - 501)	47 (12-176)	20 (5.4 - 77)	38 (10 - 143)	9.1 (2.4 - 34)	41 (11 - 156)	49 (13 - 185)	37 (10 - 138)
Pneumonia	752 (664 - 853)	77 (30-196)	34 (13 - 85)	63 (25 - 159)	15 (5.9 - 38)	68 (27 - 173)	81 (32 - 205)	60 (24 - 154)
Premature death	--	113 (22 - 223)	31 (6.0 - 60)	57 (11 - 112)	14 (2.7 - 27)	62 (12 - 122)	73 (14 - 145)	55 (11 - 108)

*includes admissions not attributable to pollutants from the wildfire

Estimates of health-related economic benefits of prevented hospital admissions and prevented deaths and estimates of intervention costs are provided in Table 8. With interventions in all homes, the central estimates of the economic benefits from avoided respiratory hospitalizations during the wildfire period range from $1 million to $5.8 million, while the economic benefits of reduced mortality range from $75 million to $416 million. The economic benefits from avoided hospitalizations for the four specific types of respiratory health effects are a subset of the economic benefits from avoided hospitalizations for all respiratory health effects. Operating HVAC system fans continuously during the wildfire period in the 6.92 million homes is projected to increase electricity costs by $110 million, approximately $16 per house. The incremental cost of purchasing higher efficiency filters for home HVAC systems and operating HVAC fans continuously is $133 million. The energy costs of operating the portable air cleaners is $16 million for the Brand X unit and $13 million for the Brand Y unit, or $2.3 and $1.9 per house, which is far lower than the energy cost for continuous HVAC fan operation. The portable air cleaners are more energy efficient than central HVAC systems in removing particles because of their lower fan power per unit air flow and higher particle removal efficiency. If the costs of portable air cleaners are included in intervention costs, total intervention costs for the $6.2 million homes range from $1.7 trillion to $4.4 trillion, although it is unlikely that large numbers of home owners would purchase portable air cleaners solely for use during a 10 day period of wildfire smoke exposure.

With interventions only in the 22% of homes housing elderly, the projected economic benefits of reduced hospitalizations remain similar in magnitude, while the projected mortality related economic benefits increase due to the aforementioned increase in projected prevented deaths. However, intervention costs decrease by almost 80%.

With interventions in all homes, the intervention costs always far exceed the economic benefits from reduced hospitalizations. However, the economic benefits of reduced mortality substantially or greatly exceed the intervention costs of interventions i1- i3 that do not use portable air cleaners. The mortality-related benefits are not sufficient to pay for portable air cleaner purchases, but greatly exceed the cost of portable air cleaner operation. With interventions only in the homes of the elderly, intervention costs still exceed the economic benefits from reduced hospitalizations. Also, the economic benefits of reduced mortality greatly exceed the intervention costs of interventions i1- i3 that do not use portable air cleaners. However, the total economic benefits from reduced hospitalizations and deaths are sufficient to pay for purchase of the less expensive Brand X air cleaners.

Table 8. Economic benefits and costs of interventions.

	Health-related economic benefits ($ million)				Intervention costs ($million)						
Intervention	All res-pira-tory	Sum of four out-comes	Mor-tal-ity	All respira-tory plus mortal-ity	Port-able air cleaner	HVAC incre-mental energy cost	HVAC incre-mental filter cost	Port-able filter energy cost	Portable filter equip-ment cost	Total cost excluding cost of portable filter equipment	Total cost including cost of any portable filter equipment
Interventions in all homes											
(i1) Low efficiency continuous	2.4 (1.5-3.7)	1.3 (0.8-2.4)	169 (33-332)	171 (34-334)	None	110 -	0	0	0	---	110
(i2) High efficiency continuous	4.5 (2.9-7.1)	2.5 (1.4-7.6)	321 (63-632)	325 (65-634)	None	110 -	23	0	0	---	133
(i3) High efficiency intermittent	1.0 (0.7-1.6)	0.6 (0.3-0.8)	75 (15-147)	76 (15-147)	None	0	23	0	0	---	23
(i4) Low efficiency continuous + Portable	4.9 (3.1-7.7)	2.8 (1.6-9.1)	349 (68-688)	354 (71-691)	Brand X	110 -	0	16	1660	126	1790
					Brand Y	110	0	13	4220	123	4350)
(i5) High efficiency continuous + Portable	5.8 (3.7-9.2)	3.3 (1.9-14)	416 (81-820)	422 (84-823)	Brand X	110	23	16	1660	149	1810)
					Brand Y	110	23	13	4220	146	4370
(i6) Portable filter unit	4.5 (2.9-7.1)	2.5 (1.4-7.6)	321 (63-633)	326 (65-636)	Brand X	0	0	16	1660	16	1680
					Brand Y	0	0	13	4220	13	4240
Interventions in homes with residents age ≥ 65											
(i1) Low efficiency continuous	1.9 (1.0 - 3.5)	1.2 (0.5 – 2.6)	245 (48 – 483)	247 (49 – 484)	None	24	0	0	0	---	24
(i2) High efficiency continuous	3.5 (1.9 - 6.5)	2.3 (0.9 – 9.3)	458 (90 – 903)	462 (91 – 905)	None	24	5.1	0	0	---	29
(i3) High efficiency intermittent	0.8 (0.5 - 1.6)	0.5 (0.2 – 0.8)	109 (21 – 215)	110 (22 – 216)	None	0	5.1	0	0	---	5.1
(i4) Low efficiency continuous + Portable	3.8 (2.1 – 7.1)	2.5 (1.0 – 11)	498 (97 – 982)	502 (99 – 984)	Brand X	24	0	3.5	365	28	393
					Brand Y			2.9	928	28	956
(i5) High efficiency continuous + Portable	4.5 (2.5 - 8.4)	2.9 (1.1 – 18)	590 (115-1163)	595 (118 – 1166)	Brand X	24	5.1	3.5	365	33	398
					Brand Y			2.9	928	32	960
(i6) Portable filter unit	3.4 (1.8 – 6.3)	2.2 (0.9 – 8.5)	442 (86 – 871)	445 (88 – 873)	Brand X	0	0	3.5	365	3.5	368
					Brand Y			2.9	928	2.9	931

DISCUSSION

Based on this analysis, interventions that increased particle filtration rates in all homes would have prevented 47 to 261 respiratory hospital admissions associated with the wildfire in Southern California in 2003. However, the fraction of the exposed population with a hospital admission attributable to wildfire smoke is small, thus, the costs of implementing filtration-based interventions in every household far exceeds the economic benefits of reduced hospital admissions. Targeting the interventions only at the homes of the elderly, i.e., homes with residents age 65 or higher, reduces intervention costs by almost 80% while health benefits remain similar in magnitude. If the elderly remain at home during the period of wildfire smoke exposure, the interventions are more effective in reducing PM2.5 intake and associated hospitalizations.

Interventions in all homes are projected to prevent PM2.5-related deaths during the wildfire period by 9 to 52, which compares to the estimated 133 total excess cardiorespiratory deaths during the wildfire period. The estimated economic value of the prevented deaths far exceeds intervention costs for interventions that do not use portable air cleaners. For the interventions that incorporate portable air cleaner use, mortality-related economic benefits exceed intervention costs as long as the cost of the air cleaners, which have a multi-year life, are not attributed to the ten day wildfire period. Cost effectiveness is improved by performing interventions on in the homes of the elderly, particularly if the elderly remain indoors at home during the period of wildfire smoke exposure.

Two studies were identified that experimentally evaluated the use of air cleaners in homes during wildfires. Barn et. al. (2008) found that portable air cleaner operation during summer wildfire periods in 17 homes reduced indoor PM2.5 from outdoors by 65 ±35%. Ratios of the air cleaners' CADR values to house volumes were not provided. Henderson et. al. (2005) studied five pairs of homes exposed to wildfire smoke, and operated air cleaners in one home of each pair. Applying a model to the data, the authors estimated that the air cleaners reduced indoor PM2.5 concentrations by 63% to 88%. Ratios of the air cleaners' CADR values to home volumes ranged from 0.85 h^{-1} to 2.37 h^{-1}, and averaged 1.8 h^{-1}. Among our scenarios, i4 and 16, are most appropriately compared to these empirical findings. In i4, a forced air system containing a typical low efficiency particle filter and a portable air cleaner with CADR of one indoor air volume per hour were operated continuously and the predicted decrease in PM2.5 in the home was 51%. In i5, there was no forced air system but an air cleaner with a CADR of one indoor air volume per hour was operated continuously and the predicted decrease in PM2.5 in the home was 45%. These predicted reductions in indoor PM2.5 are moderately lower than the empirically-measured reductions. The discrepancy between our predictions and the data of Henderson is consistent with expectations given the different ratios of CADR to home volume.

To the best of our knowledge, this paper provides the first detailed assessment of the benefits and costs of using particle filtration interventions to reduce the adverse health effects associated with a wildfire. Strengths of this analysis include the use of a model that accounts for PM2.5 exposures and inhalation throughout the day, the extensive effort given to utilize the best available values for model input parameters, and the evaluation of multiple interventions.

Data are not available to empirically validate the predicted benefits of the filtration interventions; however, use of high efficiency particle filters during a wildfire in 1999 was associated with decreased reporting of lower respiratory symptoms (Mott et. al. , 2002).

As is typical, the analysis has numerous limitations. While 43 of 45 studies reviewed by Liu et. al. (2015) found that wildfire smoke exposure increases hospital admission rates or contacts with hospitals or clinics, fewer studies have assessed the effects of wildfires on mortality and the findings have been less consistent, with nine of 13 studies reporting statistically significant increases in mortality (Liu et. al., 2015). Because the concentrations and duration of wildfire smoke exposure vary greatly among studies, variable findings are expected. Nevertheless, the predicted reductions in mortality with filtration interventions appear to be less certain than the predicted reductions in respiratory hospitalizations because wildfires are less consistently linked to mortality.

The focus of the analysis only on the period of wildfire smoke exposure is an important limitation to the analysis of prevented hospital admissions. There may have been substantial wildfire-related hospital admissions that occurred after the period of wildfire smoke exposure (Delfino et. al., 2009). The modeling did not account for reductions of any of these post-wildfire admissions.

Our analysis relied on data relating hospital admissions and deaths to increases in PM2.5 concentrations; however, some of the health effects may be attributable to wildfire-generated gaseous air pollutants such as nitrogen oxides and aldehydes. The modeling did not address the effects of the air cleaners on gaseous air pollutants.

The PM2.5 removal efficiencies of the filters used in the forced air heating and cooling systems of homes were based on typical size distributions of urban outdoor particles. If particles from wildfires tend to be smaller than typical urban-air particles, the modeling will have over-estimated reductions in indoor air particle concentrations, particularly for intervention i1 that relies on a typical low-efficiency filter.

Some of the interventions evaluated may have already been implemented in a subset of homes during the 2003 wildfire, reducing the number of homes in which the modeled interventions could be added. For example, if 10% of home owners operated portable air cleaners during the 2003 wildfire period, the health benefits of intervening in the remaining 90% of homes would be roughly 90% of our predicted health benefits. We did not find data for estimating the extent to which the interventions were already implemented.

The analysis considered only the implementation of interventions in all homes and in the subset of homes with elderly. Interventions could also be targeted at homes of residents with pre-existing respiratory or cardiovascular diseases such as asthma. Such a targeting would likely improve cost effectiveness.

Study limitations include reliance on steady state mass balance models and the assumption of well mixed indoor air; however, given the ten-day exposure period and the almost seven million homes the influence of time variable conditions and imperfect indoor air mixing are likely to average out, leading to modest associated errors. In some homes, portable air cleaners may be installed near to where people spend the majority of time leading to larger reductions in PM2.5 intake than indicated by the model. In other homes, air cleaners may be installed where people are often not located, leading to smaller reductions on PM2.5 intake than predicted. Thus, the predicted benefits of the filtration interventions should not be applied to individual homes, rather, the predictions apply to the population of homes. Spatial variability in the outdoor air PM2.5 concentration was also ignored. The analysis by Wu et. al. (2006) indicates substantial spatial variability in the outdoor PM2.5 concentration during the wildfire period. However, this spatial variability appears unlikely to substantially bias our overall results. At locations with above-average PM2.5 concentrations, the benefits of filtration interventions will be higher than modeled while at locations with lower-than-average PM2.5 concentrations, the benefits of filtration interventions will be less than modeled. The modeling of PM2.5 exposure outside of the home has been greatly simplified. The assumption that deaths are proportional to total PM2.5 intake is unverified but is probably the best possible assumption given available data, and results differed little when the exponential dose-response model was used. The modeling relied on dose-response parameters from studies that assumed no threshold in the relationship of wildfire PM2.5 concentrations with hospitalizations and deaths. For consistency, this current analysis also assumes that there are no thresholds in the dose-response relationships; however, the prior research has not proven that there are no thresholds.

There have been some changes in home characteristics and electricity prices since 2003 that will influence the effectiveness of cost of the interventions. New homes tend to be more airtight with ventilation provided mechanically. Usually, the ventilation systems (typically exhaust fans) do not filter the incoming air; however, the lower ventilation rates of new homes may increase the extent to which people are sheltered from outdoor air particles. Turning off the mechanical ventilation when smoke levels are highest would increase the extent of sheltering and may be a viable mitigation option. The cost of electricity used in calculations was based on the average residential electricity price in California in 2003, which was the year of the wildfire. Today's electricity prices are higher and today there is a more of an increase in electricity price as the quantity of electricity use increases. Consequently, the cost of electricity used in future implementations of the interventions would exceed the costs reported in this paper.

The interventions could be implemented continuously, as opposed to just during the period of wildfire smoke exposure, and reduce the adverse health effects associated with typical daily particle exposures. Prior analyses, (Fisk 2013, Zhao et. al. , 2015) indicate that filtration interventions would substantially decrease mortality attributable to particle exposures and that the associated economic benefits usually far exceed costs.

Readers should keep in mind that the filtration interventions evaluated in this paper represent one set of multiple options for reducing the adverse health effects of wildfire smoke. Other options may include relocation of the most susceptible people away from the smoke, use of respirators, prophylactic medications, and public service announcements that, for example, advise people to stay indoors with windows closed. Home envelope tightening, and use of home mechanical ventilation systems that filter incoming outdoor air, may be a viable long-term option.

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SUPPORTING INFORMATION FOR

Health Benefits and Costs of Particle Filtration Interventions in Homes during Wildfire Smoke Exposure

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SUPPLEMENTAL INFORMATION

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Nomenclature

Symbol	Parameter
A_j	Total hospital admissions in study period for health effect *j*
B_{HA}	Inhalation air intake rate when home and awake
B_O	Inhalation rate when outdoors
B_S	Inhalation rate when home and sleeping
B_V	Inhalation rate when in a vehicle
B_W	Inhalation rate when indoors away from home
C_{B1}	PM2.5 concentration at home for baseline condition B1
C_{B2}	PM2.5 concentration at home for baseline condition B1
C_N	PM2.5 concentration at home for intervention N
C_O	PM2.5 concentration outdoors
C_{OE}	Equivalent outdoor air PM2.5 concentration
C_V	PM2.5 concentration in vehicles
C_W	PM2.5 concentration when indoors away from home
D	Duty cycle, i.e., fraction of time the fan of the forced air heating and cooling system operates
E_N	Expense of intervention N
E_H	Incremental cost of high efficiency filter
E_P	Cost of portable air cleaner
F_N	Economic value of prevented deaths for intervention N
G	Electricity price
I_{B1}	Total PM2.5 intake for baseline condition B1
I_{B2}	Total PM2.5 intake for baseline condition B2
I_N	Total PM2.5 intake for intervention condition N
K_{B1}, K_{B2}	Constants relating PM2.5 concentrations in home to outdoor air PM2.5 concentration, for baseline condition B1 and B2
K_N	Constant relating PM2.5 concentrations in home to outdoor air PM2.5 concentration, for intervention condition N
K_V	Constant relating PM2.5 concentrations in vehicle to outdoor air PM2.5 concentration
K_W	Constant relating PM2.5 concentrations indoors away from home to outdoor air PM2.5 concentration
M_N	Number of deaths prevented by intervention N
N_j	Total number of hospital admissions for outcome *j* during the wildfire period
P	Particle penetration factor, i.e., the fraction of particles that penetrate through the building envelope during air infiltration
Q	Air flow rate in the home's forced air heating and cooling system divided by the indoor volume
Q_P	Air flow rate in the portable air cleaner divided by the indoor volume
R_j	Fractional reduction in hospitals admission rate for respiratory effect j
$RR_{j,post\ wildfire}$	Relative rate of hospital admissions for respiratory health outcome j during post wildfire period, assigning a relative rate of unity to the pre-wildfire period
$RR_{j,\ wildfire}$	Relative rate of hospital admissions for respiratory health outcome j during wildfire period, assigning a relative rate of unity to the pre-wildfire period
S_j	Number of prevented admissions to the hospital for respiratory effect j

T_O, T_S, T_{HA}, T_W , T_V	Time spent outdoors (subscript O), home asleep (subscript S), home awake (subscript HA) indoors away from home (subscript W), I vehicles (subscript V)
U_D	Economic value of an avoided death
U_j	Economic value of a prevented hospital admission for respiratory effect j
V	House volume
V_T	Economic value of prevented hospital admissions
X_j	Fractional change in hospital admissions for health outcome "j" per 10 μg m^{-3} change in outdoor air PM2.5 concentration
Y_j	Number of hospital admissions per day for respiratory effect *j* in the pre-wildfire period
Z	Power consumption of the forced air heating and cooling system fan per unit air flow
Z_P	Power consumption of the portable air cleaner fan per unit air flow
ε_H	PM2.5 removal efficiency of the higher efficiency filter in the forced air system during interventions i2, i3, and i5
ε_L	PM2.5 removal efficiency of the low efficiency filter normally used in the forced air heating and cooling system of the home
ε_p	PM2.5 removal efficiency of the portable air cleaner
ε_W	PM2.5 removal efficiency of the particle filter used for buildings other than the home
ΔI	Reduction in PM2.5 inhalation intake attributable to intervention
λ_D	Rate of particle removal by deposition on indoor surfaces, normalized by indoor volume
λ_{DW}	Rate of particle removal by deposition on indoor surfaces in buildings other than the home, normalized by indoor volume
λ_F	Rate of particle removal by the home's forced air heating and air conditioning system in the absence of an intervention, normalized by indoor volume
λ_{IW}	Air infiltration rate in buildings other than the home, normalized by indoor volume
λ_{MW}	Flow rate of outdoor air supplied mechanically in buildings other than the home, normalized by indoor volume
λ_N	Rate of particle removal by filtration in the home during intervention N, normalized by indoor volume
λ_{RW}	Mechanical recirculation air flow rate in buildings other than the home, normalized by indoor volume
λ_V	Infiltration ventilation rate of the home, normalized by indoor volume
λ_{VW}	total ventilation rate in buildings other than homes

Model Input Parameters

The distribution of home ventilation rate (λ_V) is shown if Figure A1. The geometric mean (GM) and geometric standard deviation (GSD) were calculated empirically from the weighted sum of three distributions based on data from Southern California homes as reported by Wilson et. al. (1996) [distributions I and ii] and Yamamoto et. al. (2010) [distribution iii]. Much of the available data are from measurements during the winter of 1985. Due to the widespread implementation, since 1985, of home envelope sealing to increase home energy performance, today's homes may have lower infiltration rates.

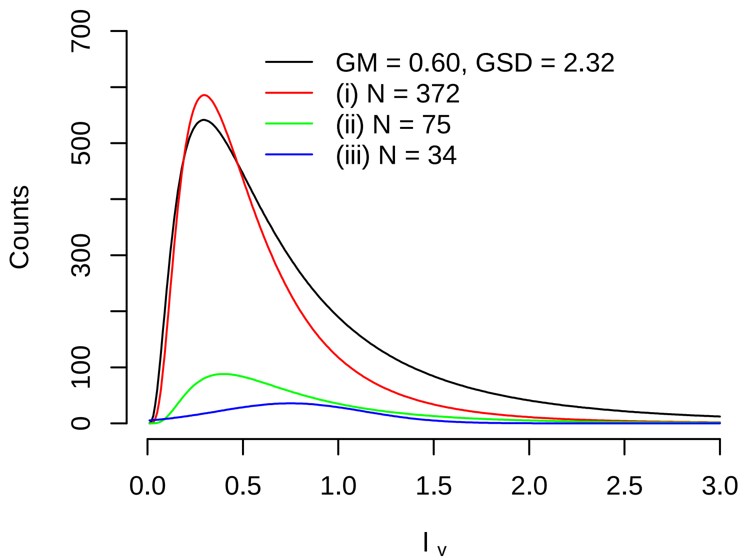

Figure S1. Residential ventilation rates.

The ventilation rates in commercial buildings (λ_{VW}), shown in Figure A2, were assumed to follow a lognormal distribution with the GM and GSD calculated from measurements from four studies (Persily and Gorfain, 2008, Bennett et. al. , 2012, Chan et. al. , 2014, Mendell et. al. , 2015). In some commercial buildings, those with economizer systems, the mechanically supplied ventilation rates are set to a minimum when it is warm outdoors and energy-intensive cooling is needed. Other commercial buildings have no economizers so the mechanical ventilation rate is not modulated over time. During the 2003 wildfire period, weather was sufficiently hot to deactivate economizers, when present, resulting in minimum ventilation rates. Only one of the three studies (Mendell et. al., 2015) provided data for calculating minimum ventilation rates. These data are used together with the measured ventilation rates from the other studies, which likely exceeded minimum rates in the subset of buildings that had economizers. For the modeling, the total ventilation rate, for λ_{VW}, must be apportioned into ventilation by infiltration (λ_{IW}) and mechanical ventilation (λ_{MW}). Very few data are available on infiltration-based ventilation rates in commercial buildings and the available data are almost exclusively from periods with no mechanical ventilation. During periods of mechanical ventilation, in many buildings the rate of infiltration is reduced because the mechanical ventilation systems seek to slightly pressurize buildings. Based on the analysis of Rackes and Waring (2015), we assumed a value of 0.1 h^{-1} for λ_{IW}. Fortunately, the results of this analysis are not highly sensitive to the commercial building ventilation rates.

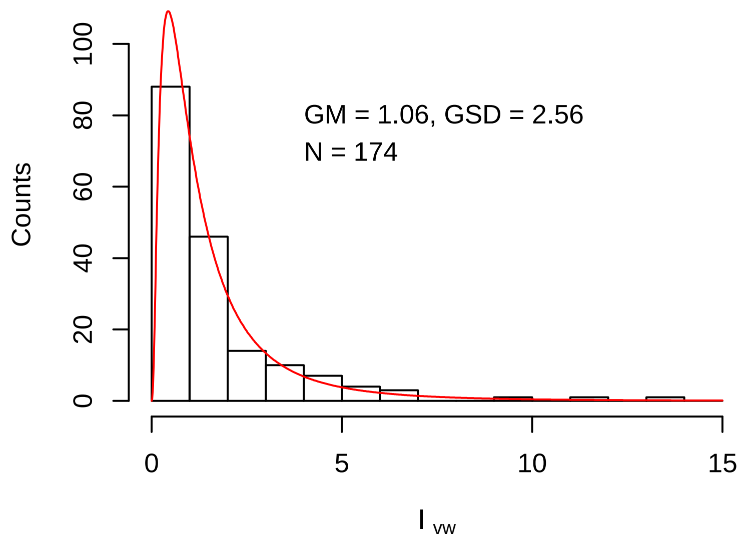

Figure S2. Workplace ventilation rates.

The mechanical recirculation air flow rate (λ_{RW}) shown in Figure A3 was based on data from (Persily and Gorfain, 2008). A curve fit to the cumulated distribution (red line) is used to model this parameter. The associated frequency data are shown in Table A1

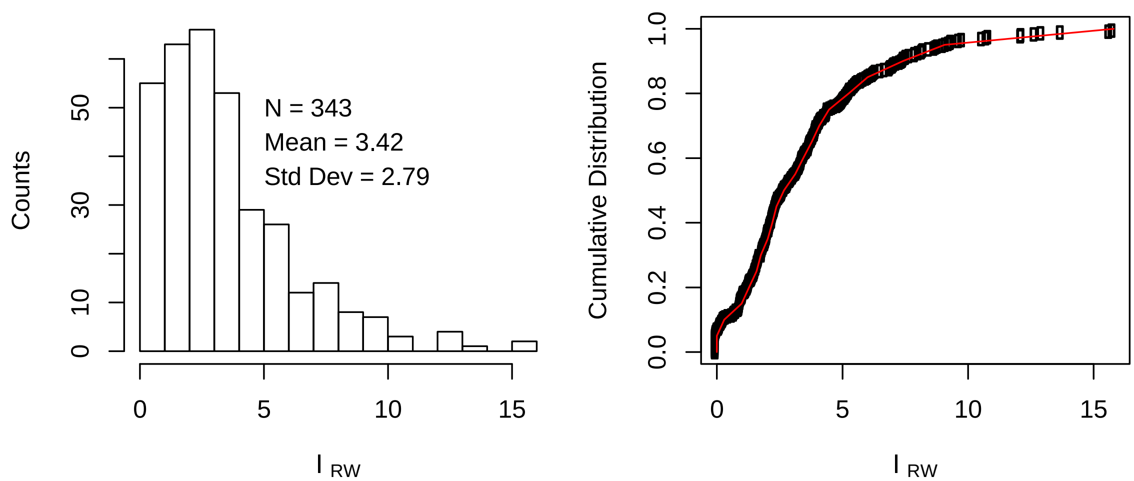

Figure S3. Air recirculation rates at workplaces.

Table S1. Cumulative distribution of mechanical recirculation air flow rate (λ_{RW}).

Percentile	λ_{RW}	Percentile	λ_{RW}	Percentile	λ_{RW}
0.02	0	0.35	2.02	0.7	4.07
0.05	0	0.4	2.21	0.75	4.46
0.1	0.29	0.45	2.37	0.8	5.25
0.15	0.98	0.5	2.67	0.85	6.00
0.2	1.28	0.55	3.12	0.9	7.41
0.25	1.58	0.6	3.44	0.95	9.06
0.3	1.75	0.65	3.77	0.99	12.2

The penetration factor (P),shown in Figure A4, was assumed to follow a cropped normal distribution with values between 0 and 1. The mean and standard deviation of the normal distribution were weighted values calculated from measurement in 37 homes by Williams et. al. (2003) and 293 homes by Ozkaynak et. al. (1996).

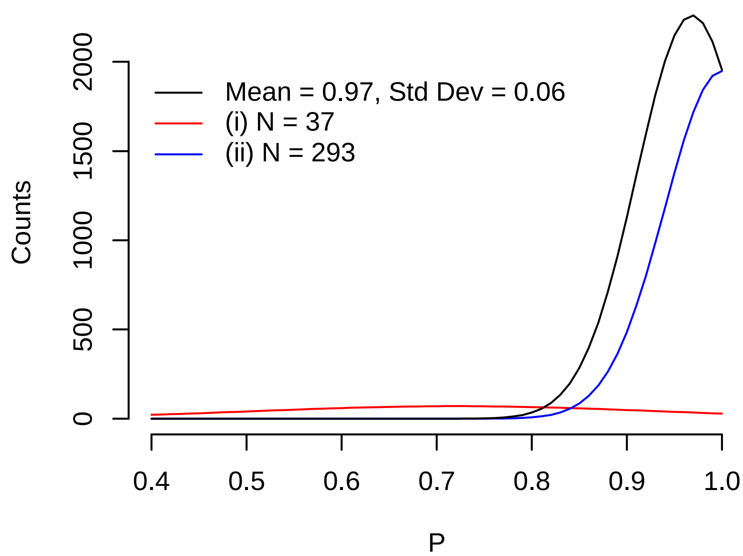

Figure S4. Penetration factor.

The rate of particle removal by deposition on indoor surfaces (λ_D) shown in Figure A5 was assumed to follow a normal distribution. The mean and standard deviation of the normal distribution were weighted values calculated from measurements in 37 homes by Williams et. al. (2003) and in 293 homes by Ozkaynak et. al. (1996).

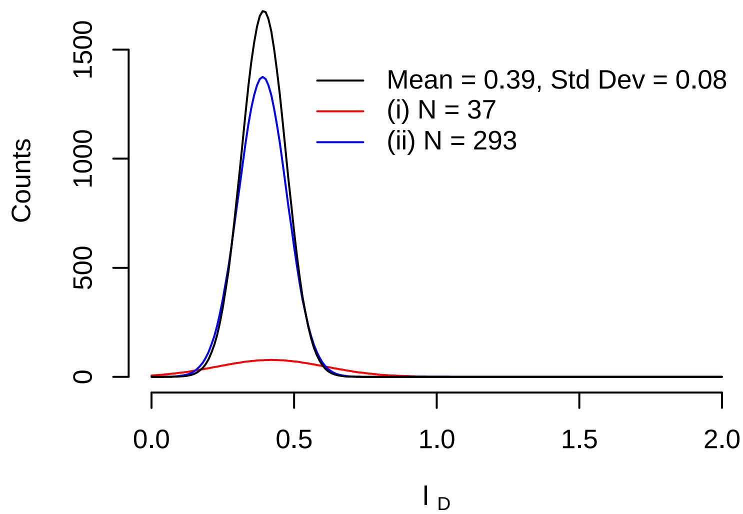

Figure S5. Rate of particle removal by deposition on indoor surfaces (λ_D).

The air flow rate of the forced air heating and air conditioning system in homes divided by the indoor volume (Q) is shown in Figure A6. The GM and GSD were calculated from measurements from two studies (Stephens et. al. , 2011, Jump et. al. , 1996).

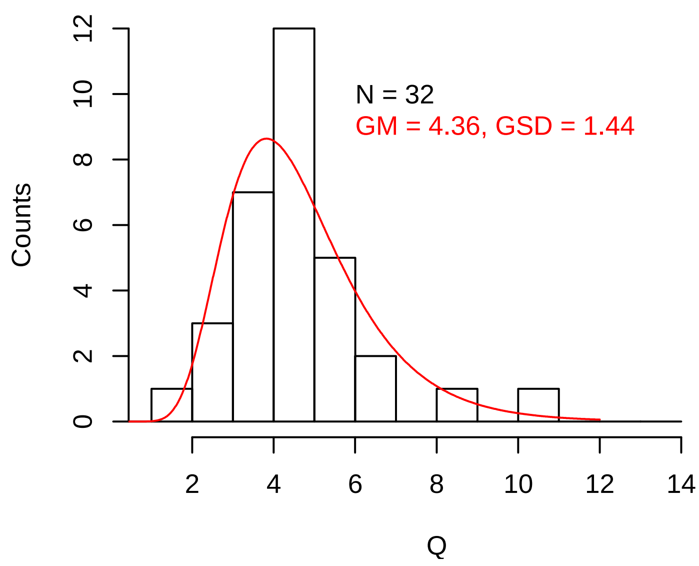

Figure S6. Air flow rate of home forced air heating and air conditioning systems in homes.

The fraction of time that the forced air fan in the home operates (D), sometimes called the duty cycle, was assumed to follow a cropped normal distribution with values between 0 and 1 and is shown in Figure A7. By far, the largest study of duty cycle is a study of 189 homes for a full year by Cetin and Novoselac (2015). Based on this study, a duty cycle for southern California homes during the 2003 wildfire was derived using a polynomial equation relating duty cycle with outdoor air temperature together with historical temperature data during the 2003 wildfire period from a major city in each county, with weighting by the population in each county.

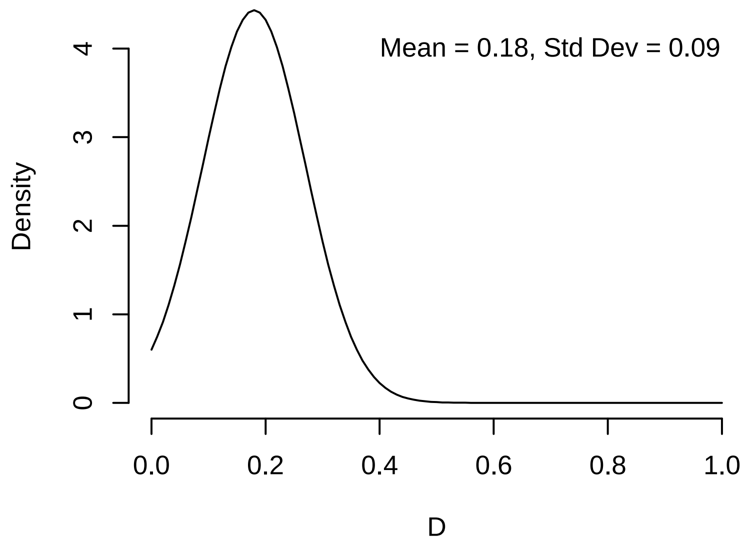

Figure S7. Duty cycle.

The distributions of PM2.5 removal efficiency of particle filters are show in Figure A8. The parameter ε_L is the PM2.5 removal efficiency of the low efficiency filter normally used in a residential forced air system, ε_H is the PM2.5 removal efficiency of the higher efficiency filter in the forced air system during interventions (averaging data for MERV 8 and MERV 10 filters), and ε_W is the PM2.5 removal efficiency of filters in workplaces. The distributions of filter efficiency are assumed to follow a cropped normal distribution, with values between 0 and 1. The PM2.5 removal efficiency of the standard low efficiency filters in residential forced air systems was based on a small study of the efficiency ratings of filters used in homes (El Orch et. al. , 2014), a downward adjustment of efficiency rating for the few higher efficiency filters to account for air leakage around high efficiency filters installed in homes (VerShaw et. al. , 2009), and the PM2.5 removal efficiency of filters with different efficiency ratings (Azimi et. al. , 2014). For interventions i2 and i4, we assumed use of a higher efficiency filter, with a Minimum Efficiency Reporting Value (MERV) rating of 12, in the forced air systems of homes. However, based on estimates of the extent of air leakage around filters in residential forced air systems, the effective MERV rating for a MERV 12 filter was assumed to be MERV 9 (VerShaw et. al., 2009). Azimi et. al. (2014) provide PM2.5 removal efficiencies for MERV 8 and MERV 10 filters, and the average of these two reported efficiencies was employed in calculations. For work places, we assumed a MERV 8 filter and used efficiency data from (Azimi et. al., 2014).

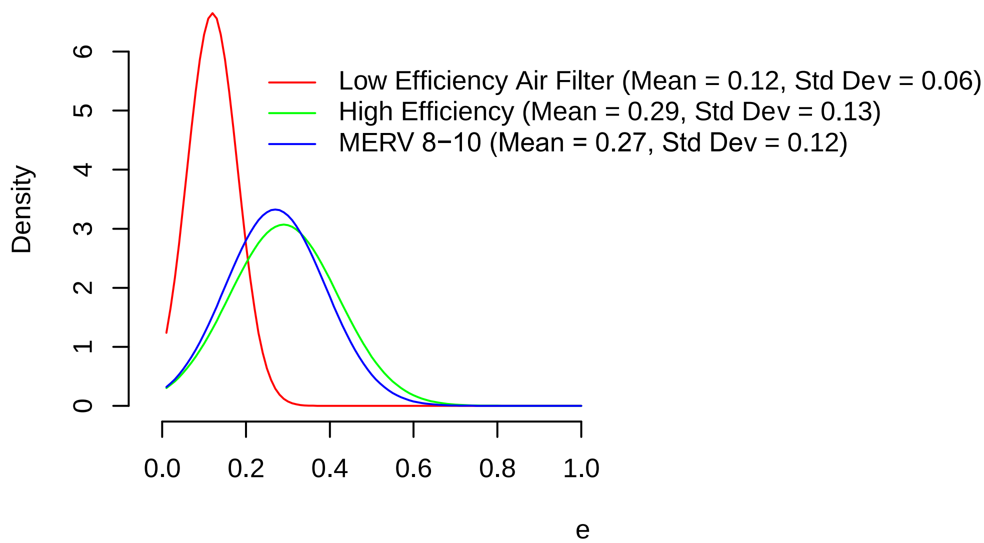

Figure S8. PM2.5 removal efficiency values of filters.

The ratio of PM2.5 concentrations in vehicles to outdoor air concentrations (K_V), shown in Figure A9, was assumed to follow a cropped normal distribution with values between 0 and 1. This distribution was based on the very limited data identified from the U.S. for cars with closed windows (Rodes et. al. , 1999). The four reported values ranged from 0.58 to 0.71.

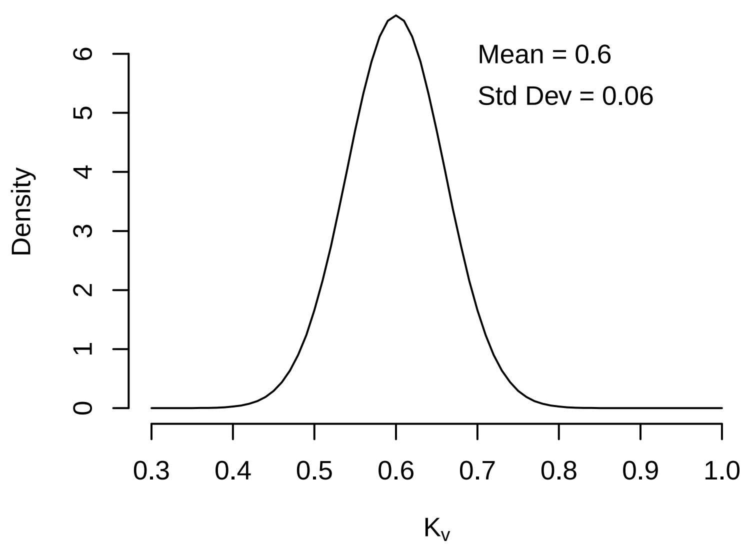

Figure S9. Ratios of PM2.5 concentrations in vehicles to outdoor air concentrations.

House volumes (V) were estimated assuming an average ceiling height of 2.7 m and using floor-area data for the Anaheim-Santa Ana, Los Angeles-Long Beach-Santa Ana, Riverside-San Bernardino-Ontario, San Diego-Carlsbad-San Marcos metropolitan areas (U.S. Census Bureau, 2011). House volumes approximately follow a lognormal distribution indicated by the red line in Figure A10.

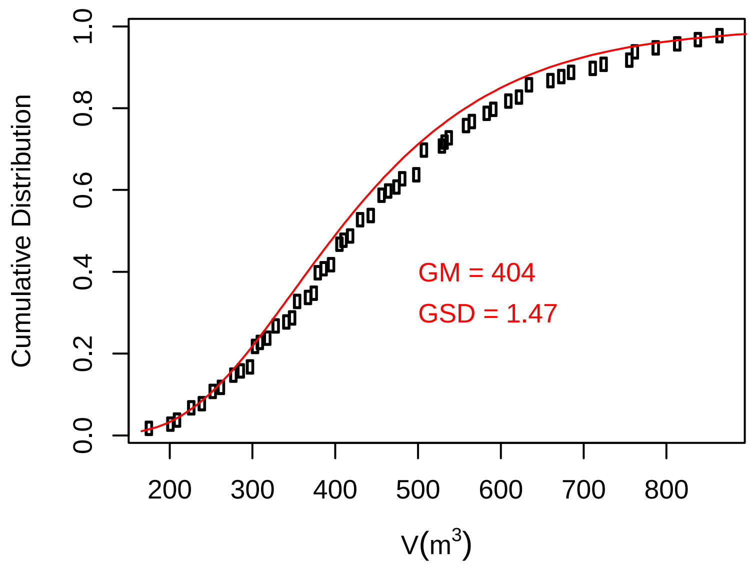

Figure S10. House volume.

Table A2 provides the model input values for times in different environments and inhalation rates. The percentage times in environment types is based on the National Human Activity pattern Survey (Klepeis et. al. , 2001) with time spent sleeping based on the data from U.S. EPA's Exposure Factors Handbook (EPA, 2011) combined with data on population versus age (U. S. Census Bureau, 2014). The small error estimates in the mean percentages of time spent in environment types was based on a comparison of means from the National Human Activity Pattern Survey and the California Activity Pattern Survey (Klepeis et. al., 2001).

Although detailed data are available on fraction of time at different metabolic rates and inhalation rates as a function of metabolic rate, insufficient data were identified to characterize, in detail, metabolic rates that occur in different locations. Total daily inhalation rates as a function of age are available (EPA, 2011) and were used together with population data (U. S. Census Bureau, 2014) by age for the six-county region to estimate average total daily inhalation rates for all ages and for the sub population with age of twenty or higher. We assumed that people have the same average inhalation rate when awake at home, at other indoor locations, and in vehicles. We were able to estimate that average inhalation rates when sleeping are 81% of inhalation rates when home and awake (EPA, 2011, Roy and Courtay, 1991) and that the average inhalation rate when outdoors is, on average, 26% higher than the inhalation rate when indoors (23% for the sub population with age of twenty or higher). Analyses of these data yielded the estimates of inhalation rates B_O, B_S , B_{HA} , B_W , B_V , within Table A2. Insufficient data were available to calculate estimates of the uncertainties in mean inhalation rates without assumptions. For uncertainty estimation we have assumed uncertainties of ± 25%.

Table S2. Times and inhalation rates in different environment types.

Location	All Ages		Age ≥ 20		Age ≥ 65	
	Time [estimated variability] (%)	Inhalation rate [estimated variability] ($m^3 h^{-1}$)	Time [estimated variability] (%)	Inhalation rate [variability] ($m^3 h^{-1}$)	Time (%)	Inhalation rate [estimated variability] ($m^3 h^{-1}$)
Home at sleep	37.0 [36 – 38]	0.58 [0.43 – 0.72]	34.6 [33.6 – 35.6]	0.61 [0.46 – 0.76]	36.2	0.52 [0.39 – 0.65]
Home awake	32.0 [31 – 33]	0.71 [0.53 – 0.89]	33.6 [32.6 – 34.6]	0.75 [0.57 – 0.94]	63.8*	0.64 [0.48 -0.80]
Other indoor	17.9 [16.9 – 18.9]	0.71 [0.53 – 0.89	18.6 [17.6 – 19.6]	0.75 [0.57 – 0.94]	0*	---
Outdoor	7.5 [6.5 – 8.5]	0.83 [0.62 – 1.03]	7.2 [6.2 – 8.2]	0.86 [0.65 – 1.08]	0*	---
Vehicle	5.5 ± 1 [4.5 to 5.5]	0.71 [0.53 – 0.89	5.9 [4.9 – 6.9]	0.75 [0.57 – 0.94]	0*	---

*scenario assumes this subpopulation is home 100% of the time during the period of wildfire smoke exposure, normally they are home 81% of the time (Klepeis et. al., 2001)

Supplemental Results

The predicted cumulative distributions of PM2.5 concentrations are shown in Figure A11.

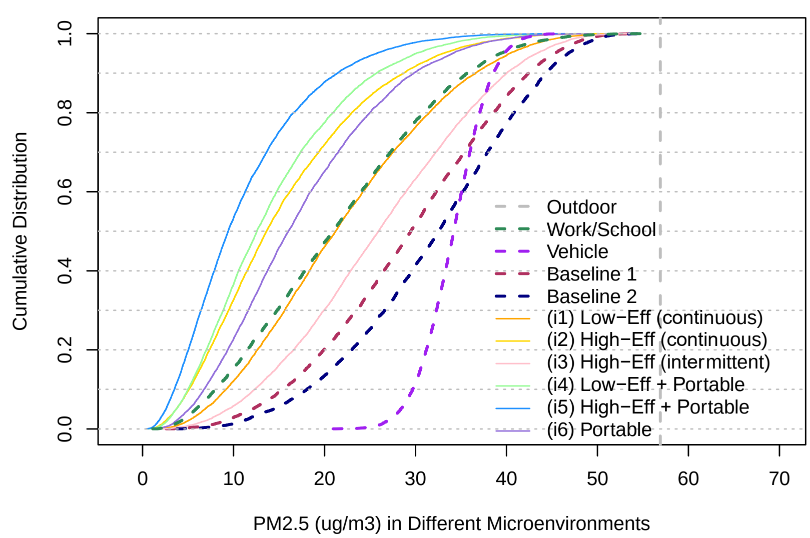

Figure S11. Predicted cumulative distributions of PM2.5 concentrations.

The Boxplots in Figure A12 show 5th, 25th, 50th, 75th, and 95th percentiles of PM2.5 intake rates. The point values are the predicted population mean PM2.5 intake rates. Equivalent outdoor air PM2.5 concentrations are provided in Table A3.

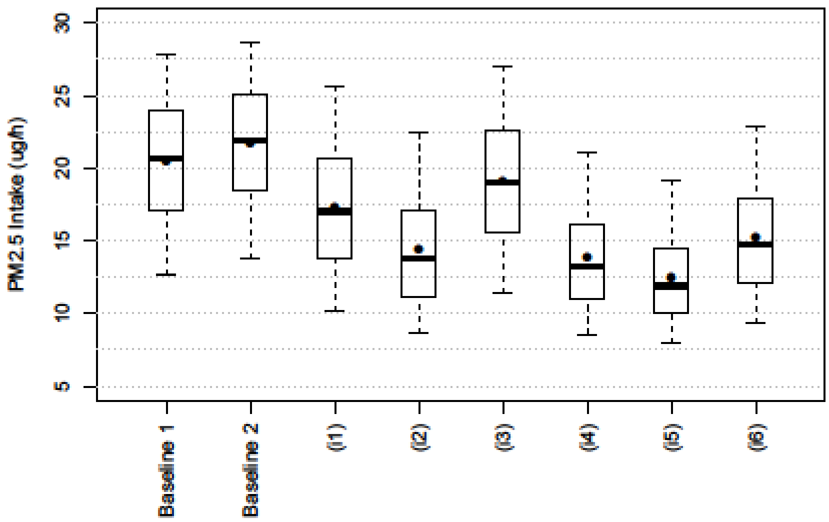

Figure S12. PM2.5 intake rates for baseline cases and with interventions in all homes.

Table S3. Predicted population mean equivalent outdoor air PM2.5 concentration C_{OE} when the outdoor air PM2.5 concentration is 56.9 ug/m^3.

Interventions	C_{OE} **(All Ages)**	C_{OE} **(Age ≥ 20)**	C_{OE} **(Age ≥ 65)**
(i1) Low efficiency air filter (continuous operation)	47.9	48.0	41.5
(i2) High efficiency air filter (continuous)	39.8	39.9	28.2
(i3) High efficiency air filter (intermittent)	52.9	52.9	50.1
(i4) Low efficiency air filter (continuous) + portable filter unit	38.3	38.4	25.7
(i5) High efficiency air filter (continuous) + portable filter unit	34.8	34.8	19.9
(i6) Portable filter unit	39.8	39.8	29.2

Table S4. Summary of health benefits and costs of interventions that reduce indoor exposure to $PM_{2.5}$ during wildfires*

Baseline or Intervention code	Reference Condition	Conditions			Interventions in All Homes		Interventions in Homes w/ Resident Age ≥ 65	
		Forced Air System Operation	Efficiency of Filter in Forced Air System	Continuously Operating Portable Air Cleaner	% Hospital Admissions Avoided	% Premature Deaths Avoided	% Hospital Admissions Avoided	% Premature Deaths Avoided
B1	**NA**	**Intermittent**	**Typical low**	**No**				
B2	**NA**	**No forced air**	**NA**	**No**				
i1	B1	Continuous	Typical low	No	25	16	43	27
i2	B1	Continuous	Upgraded to high	No	48	30	81	50
i3	B1	Intermittent	Upgraded to high	No	11	7	20	12
i4	B1	Continuous	Typical low	Yes	53	32	88	55
i5	B1	Continuous	Upgraded to high	Yes	63	39	100+	65
I6	B2	No forced air	NA	Yes	48	30	78	49

*Table notes

- Combined benefits of avoided respiratory admissions and avoided premature deaths outweigh implementation costs in all cases
- For cases with portable air cleaners, assumes cost of portable air cleaner purchase is not attributed to wildfire period
- Health benefits are increased and cost effectiveness is improved when considering only homes of elderly (≥ age 65), assumed to stay indoors at home during entire wildfire period

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